

Asynchronous Dictionary Learning for Remote Sensing Imagery Classification Kirtus Leyba^{1,3,4} and Prerna Patil^{1,2}



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Introduction

Machine learning is an active area of research in the science and engineering domains. Among its many applications, machine learning has been used to classify hyperspectral imaging data. Large datasets and high computational complexity serve as barriers that limit the practical use of machine learning algorithms. As a potential technique to sidestep these barriers we took the novel approach of applying an asynchronous machine learning algorithm. We also evaluated the capability for such algorithms to be parallelized and refitted for high-performance computing resources.

Algorithms

In order to generate a classification of our hyper-spectral imaging data, we needed to solve the following sparse coding problem:

argmin, subject to
$$||D\alpha - x||_2 \le \epsilon$$

Where α represents a coefficient vector, D is a dictionary of atoms, and x is a signal from the data. Once this **objective function** is minimized, the resulting coefficient vector can be used to determine a classification of the data signal x.

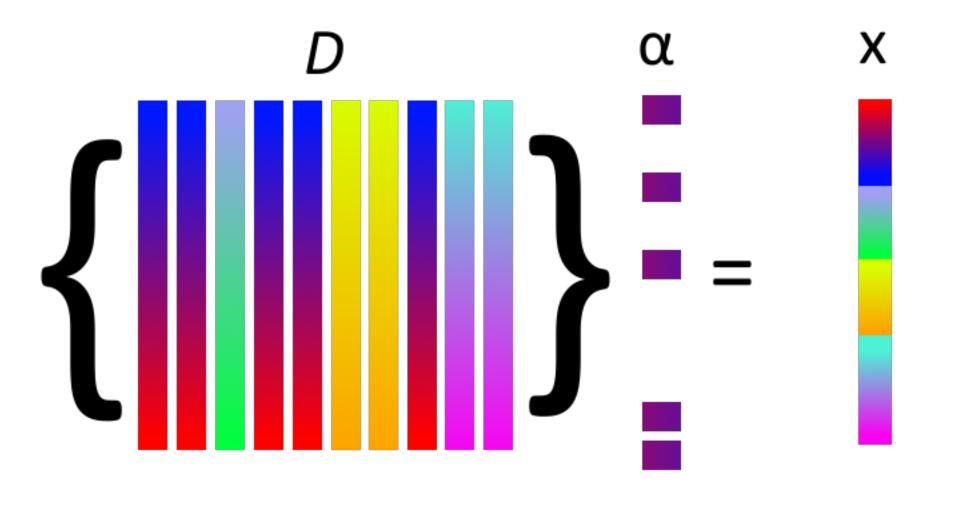
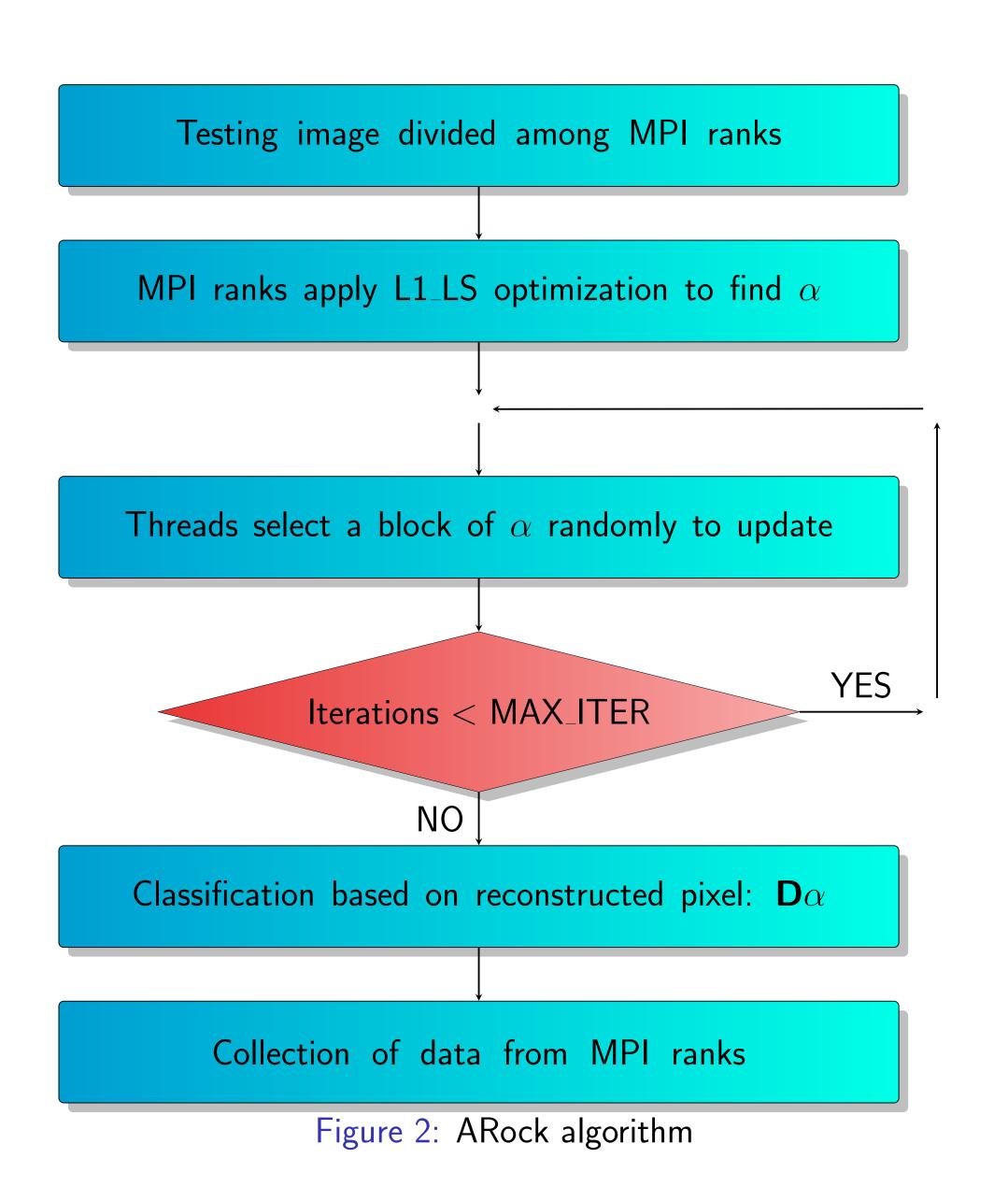


Figure 1: Visual representation of the sparse coding dictionary learning problem



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Original Pixel Data And Reconstructed Data -- Reconstructed Pixel 0.12 **Actual Pixel**

Band Number Figure 3: Pixel reconstruction for ARock

100

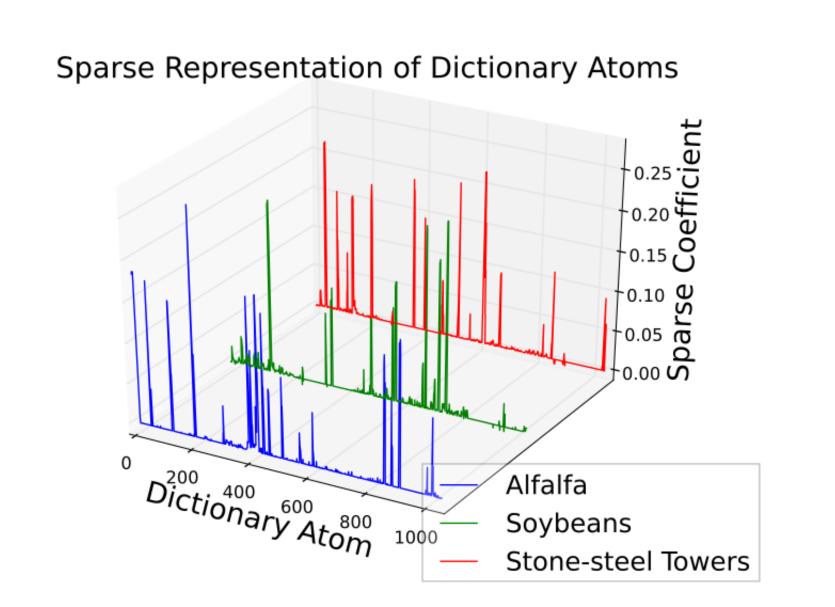


Figure 4: Sparse representation of pixel data generated by ARock

Performance

Reconstruction

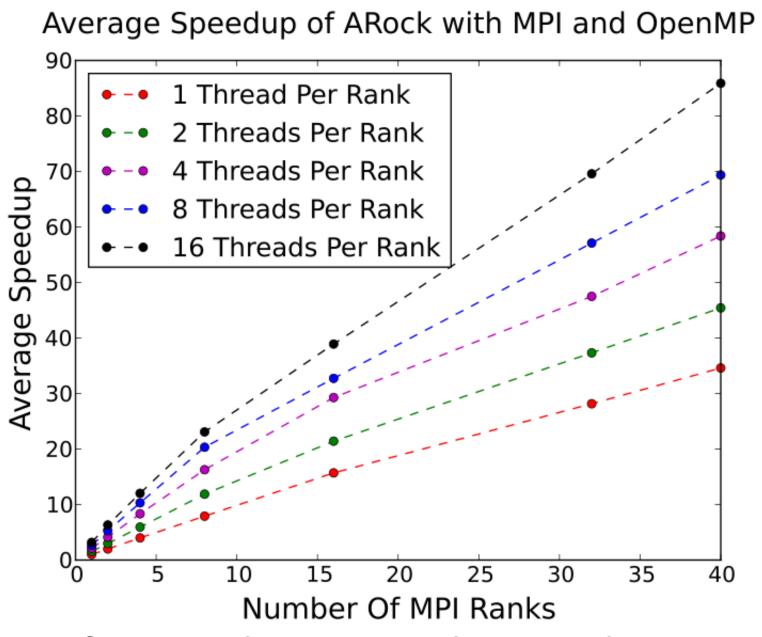


Figure 5: Speedup of ARock as a function of MPI ranks and OpenMP threads. All tests were carried out with round robin node distribution on 10 Intel E5-2695v4 Broadwells with hyperthreading

Speed Up of BPDN using MPI ●● BPDN-IRLS MPI Speed Up -- Ideal Speed Up Number of MPI ranks

Figure 6: Speedup of baseline BPDN algorithm across multiple MPI ranks. All tests were carried out with round robin node distribution on 10 Intel E5-2695v4 Broadwells with CTS-1 scalable architecture

Asynchronous Methods

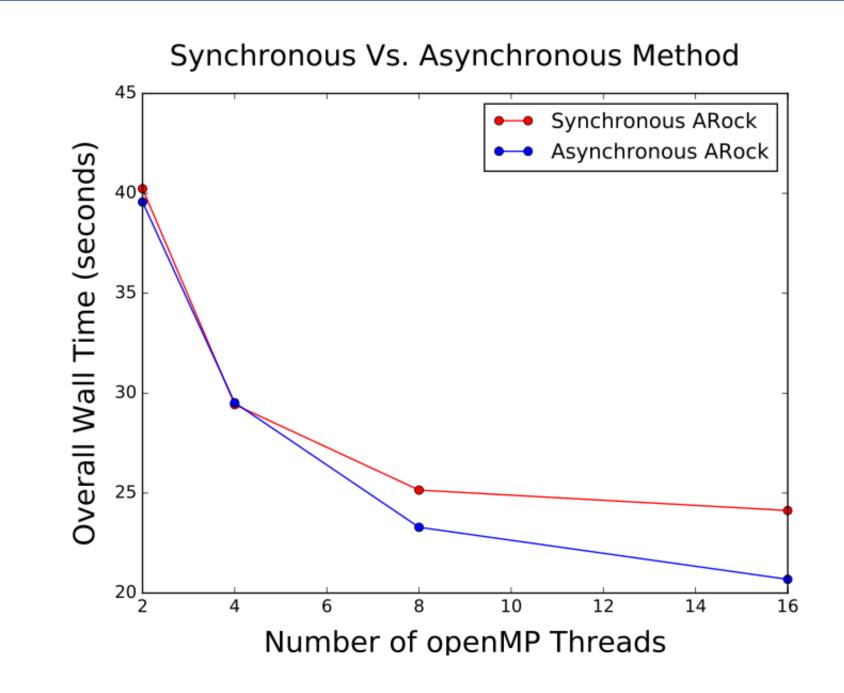


Figure 7: The performance gain from utilizing asynchronous techniques in the ARock algorithm

Classification

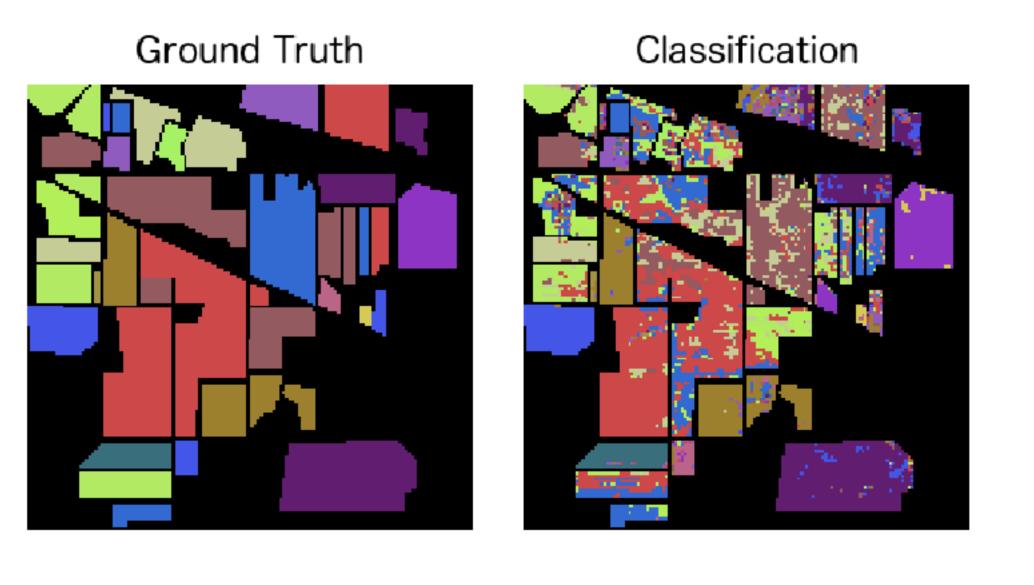


Figure 8: The ground truth and classification of the hyperspectral imaging data

Future Work: Spatial Information

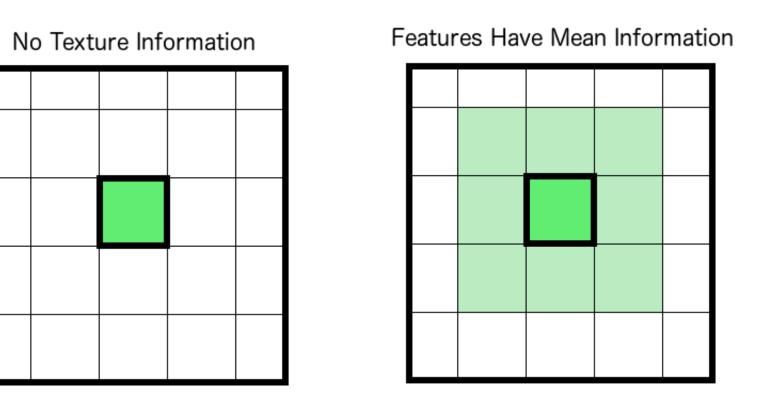


Figure 9: Current research in classification algorithms suggest that including the texture or spatial information (such as the mean and standard deviation across neighboring pixels) will result in a more accurate classification. Future work entails implementing such spatial consideration into the asynchronous ARock technique.

Conclusions

We have shown that the practices of parallelism in high-performance computing are readily applicable to machine learning algorithms. Sparse dictionary learning problems feature easily divisible problem domains, that yield well to parallel techniques on multiple scales. Our efforts were successful in simultaneously dividing large problems into chunks that can be worked synchronously, as well as dividing individual subproblems into problems that can be solved asynchronously with minimal communication. We have also demonstrated that the ARock asynchronous algorithm set provides a fast and reliable method for classifying hyper-spectral imaging data.

References

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